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Trends in Life Cycle Greenhouse Gas Emissions of Future Light Duty Electric Vehicles

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ABSTRACT

The majority of previous studies examining life cycle greenhouse gas (LCGHG) emissions of battery electric vehicles (BEVs) have focused on efficiency-oriented vehicle designs with limited battery capacities. However, two dominant trends in the US BEV market make these studies increasingly obsolete: sales show significant increases in battery capacity and attendant range, and are increasingly dominated by large luxury or high-performance vehicles. In addition, an era of new use and ownership models may mean significant changes to vehicle utilization, and the carbon intensity of electricity is expected to decrease. Thus, the question is whether these trends significantly alter our expectations of future BEV LCGHG emissions.

To answer this question, three archetypal vehicle designs for the year 2025 along with scenarios for increased range and different use models are simulated in an LCGHG model: an efficiency-oriented compact vehicle; a high performance luxury sedan; and a luxury sport utility vehicle. While production emissions are less than 10% of LCGHG emissions for today's gasoline vehicles, they account for about 40% for a BEV, and as much as two-thirds of a future BEV operated on a primarily renewable grid. Larger battery systems and low utilization do not outweigh expected reductions in emissions from electricity used for vehicle charging. These trends could be exacerbated by increasing BEV market shares for larger vehicles. However, larger battery systems could reduce per-mile emissions of BEVs in high mileage applications, like on-demand ride sharing or shared vehicle fleets, meaning that trends in use patterns may countervail those in BEV design.

Key words: EVs, batteries, LCA, carbon footprint, electric mobility, shared mobility

1. Introduction

Transportation comprises 28% of US greenhouse gas (GHG) emissions, 60% of which come from light-duty vehicles (LDVs) (US Environmental Protection Agency, 2018). While a multipronged approach is needed to achieve deep reductions in transportation GHG emissions, rapid and extensive deployment of battery electric vehicles (BEVs) is viewed as a crucial part of nearly all strategies (Alexander, 2015a; Meszler et al., 2015; Sperling, 2018). BEVs are typically referred to as zero emissions vehicles (ZEVs) because they eliminate tailpipe pollution. However, as with other de-carbonization policies for the transport sector, such as those that promote biofuels, a life cycle perspective is required to understand the actual mitigation achieved by ZEVs, since emissions are not eliminated, but rather shifted upstream in the fuel cycle (to the power plant) and potentially increased in the vehicle production supply chain. BEVs can also have considerable variability in life cycle operation emissions given the heterogeneity of electricity grids over space and time (Cerdas et al., 2018; Tamayao et al., 2015; Yuksel and Michalek, 2015).

Numerous life cycle-based studies have been conducted with the goal of verifying if BEVs (including plug-in hybrid electric vehicles (PHEVs)) achieve real reductions in emissions relative to internal combustion engine vehicles (ICEVs, including hybrid electric vehicles (HEVs)). These studies suggest that GHG emissions associated with energy for BEV operation (i.e. production of electricity) can be 44% - 80% of BEV LCGHG emissions. For non-operation GHG emissions, energy required for manufacturing of LIBs is the primary driver of increased

GHG emissions relative to ICEVs (Peters et al., 2017). Uncertainty about battery manufacturing and a lack of primary data have contributed to a wide range of results for GHG emissions associated with battery production (Ambrose and Kendall, 2016; Ellingsen et al., 2014). Moreover, given the growth in BEV sales, the evolution of BEV designs and model availability, and declining prices for traction batteries (Nykvist and Nilsson, 2015), previous life cycle assessments (LCAs) may not be representative of current and future BEV performance, vehicle specifications, or patterns of use.

1.1 Review of Literature and Relevant Data

A review of previous LCAs (here we use the term LCA to refer both to comprehensive LCAs that track a suite of environmental impacts as well as those that narrowly assess GHG emissions), a selection of which are summarized in Table 1, shows that most studies used the early generations of the Nissan Leaf as the exemplar BEV (Archsmith et al., 2015; Ellingsen et al., 2014; Graff Zivin et al., 2014; Hawkins et al., 2013; Majeau-Bettez et al., 2011; Samaras and Meisterling, 2008; Tamayao et al., 2015). Because of this, most previous LCAs have used similar assumptions, including the ~24 kWh battery capacity and efficiency-oriented compact vehicle design. Many of the earliest LCA studies of BEVs found that emissions from the electricity grid used for charging were the most significant contributor to life cycle CO_2e emissions from BEVs (Hawkins et al., 2012; Michalek et al. 2011). Justifiably, more recent studies have focused on interactions of BEVs and the electricity system, examining the consequential effects of replacing ICEVs with BEVs, and the intersection of charging strategies with the marginal dispatch decisions of electric utilities (Archsmith et al., 2015; Jenn et al., 2016; Yuksel and Michalek, 2015). At least one study has considered the effect of battery range and vehicle size on BEV performance (Ellingsen et al., 2016). They found commensurate increases in LCGHG with increasing battery and vehicle size and, similar to previous studies, found that electricity grid carbon intensity determined the preference of BEV vehicles over their conventional fossil fuel counterparts.

TABLE 1 Review of Selected Vehicle and Performance Characteristics from Life Cycle Studies of BEVs and Gasoline Vehicles

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle Production Emissions (kg CO_2e)	Battery Production Emissions (kg CO_2e)	Vehicle Operation Emissions (g CO_2e/km)
Samaras and Meisterling (2008)	PHEV	20.1	7800	2420	40.0
Notter et al. (2010)	BEV	34.2	6200	1800	101
Majeau-Bettez et al. (2011)	BEV	24	7200	4704	
Dunn et al. (2012)	BEV	28	7000	1092	
Hawkins et al. (2013)	BEV	24	7813	4620	
Ellingsen et al. (2014)	BEV	26.6		6400	
Graff Zivin et al. (2014)	BEV	24			69 – 293
Miotti et al. (2016)	BEV	19 – 60	7360	1090	120 – 185
Tamayao et al. (2015)	BEV	24	2444	4124	41 – 144
Kim et al. (2016)	BEV	24	7500	3400	
Archsmith et al. (2016)	BEV	28	7710	1542	124 – 194
Ellingsen et al. (2017)	BEV	60		6390	
Average ICEV (N=8 Studies, see table S1.1 for details)	ICEV		8294		191.5
Average HEV (traction battery included in vehicle production; N=6 Studies, see table S1.1 for details)	HEV		9420		195

While previous studies provided valuable insights about the life cycle performance of vehicles and the importance of electricity grid emissions (whether modeled as marginal or average emissions), the majority of these studies reflect outmoded assumptions about BEV vehicle designs and did not reflect trends in the BEV market. A review of US BEV sales between 2012 and 2018 shows a marked shift towards significantly higher capacity batteries, longer vehicle ranges, and an increasing preference for high performance and luxury BEVs. The combined effect of these two trends is evident in Figure 1, which shows the US sales-weighted average annual increase in BEV battery capacity of 6.5 kWh per year between the first quarter of 2012 and the second quarter of 2018, reaching 74 kWh by the second quarter of 2018. As the market for BEVs has grown, so too have the number of BEV models available. Instead of the efficiency-oriented compact passenger vehicle, the fastest selling BEV in the US has become the leader in the luxury sedan segment (Alternative Fuel Data Center, 2018). Sport-utility BEVs have emerged as an important market segment with several major vehicle manufacturers launching cross-over style BEVs (Gale, 2018).

Two important trends in personal mobility are also changing the use-cases for BEVs: one, the increased use of and participation in on-demand ride sharing services; and two, increased reliance on automated and connected vehicle technologies to replace human driving activities (Greenblatt and Shaheen, 2015). While the net effects of these trends on vehicle travel is still unknown, the emergence of ride-hailing services like Uber and Lyft are having significant impacts on traditional modes (e.g. transit) and historical patterns of mobility (Clewlow and Mishra, 2017; Hall et al., 2018). Based on early research, individual shared or automated vehicles could generate three to four times the comparable annual VMT of a conventional (private) passenger vehicle (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Loeb et al., 2018). Vehicles participating in ride-hailing services can also experience significant mileage from return links, also known as dead-heading (Henao, 2017). While induced VMT has important implications for climate and environmental policy, use of shared, automated vehicle technologies (SAVs) could increase access to mobility, particular for vulnerable, disadvantaged, or mobility challenged populations (Harper et al., 2016).

While it is easy to point out the problem of LCAs that rely on existing technologies to shape future choices or decision-making, the challenge of predicting the performance of emerging technologies, particularly those that have the potential to transform a sector or induce consequential changes in other sectors, is enormous. A number of researchers have proposed frameworks and approaches to improve prospective modeling of technologies (e.g. Miller and Keoleian (2015)). Many researchers have also highlighted the problem of data availability in the context of prospective assessments or emerging technology assessments, noting not only the challenge of modeling the performance of a technology not yet in the market, but also the lack of temporally appropriate background data for prospective assessment (e.g. Hetherington et al. 2014; Arvisson et al. 2018). To create a practicable scope of assessment, this study focuses only on trends in electric vehicle design with respect to performance characteristics and battery capacity, and considers changes to only a few background systems (e.g. the electricity grid).

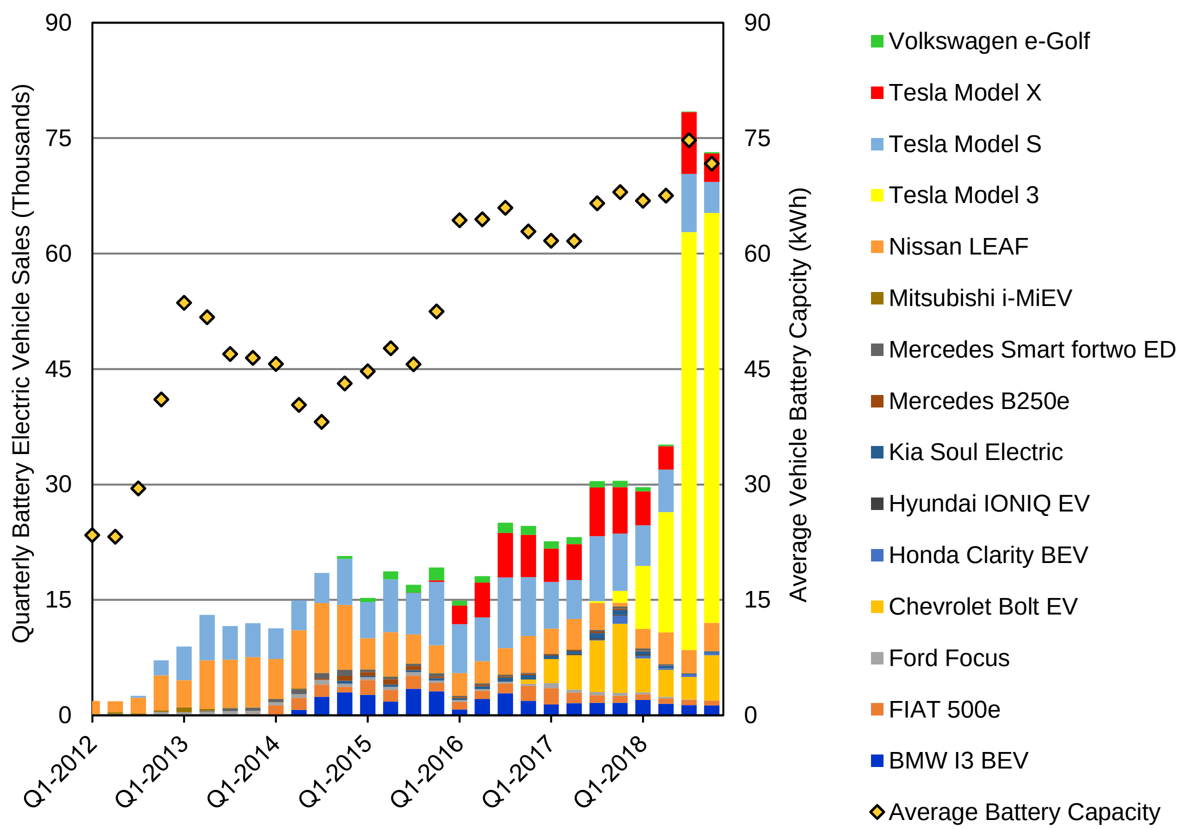

FIGURE 1 BEV sales and battery capacities in the US

The combined effects of larger battery capacity; a shift towards large, high-performance BEV models; and the increased use of BEVs in high-mileage applications may challenge some of the widely accepted conclusions of earlier BEV LCAs, namely the small contribution of vehicle production-related emissions to life cycle emissions and that in many parts of the US (and in regions throughout the world) BEVs provide GHG mitigation benefits (albeit sometimes small) relative to ICEVs. This observation led to the following research questions explored in this study:

(1) How do current trends in BEV vehicle design, including increased battery capacity and high performance and luxury vehicles, affect LCGHG intensity of vehicle?

(2) What is the combined effect of vehicle design trends and technology and electricity grid evolution on the LCGHG emissions intensity of BEVs?
(3) How will these trends effect future emissions rates of BEVs, particularly in high-mileage applications like shared ride fleets

2. Methodology

2.1 Goal and Scope

This study aimed to quantify the LCGHG emissions of three archetypal future BEVs that reflect the changing BEV market, as described below:

Archetype 1 - An efficiency-oriented compact vehicle (EOV), based on the Chevrolet Bolt.
Archetype 2 - A high performance luxury sedan (PLS), based on the Tesla Model S P100D.
Archetype 3 - A high performance SUV (PSUV), based on the Tesla Model X P100D.

For each vehicle archetype, the study considers how future changes in vehicle design, battery performance, changing electricity grid, and annual mileage will affect the total LCGHG emissions of the vehicle. Results are presented in a functional unit of vehicle mile travelled (VMT), where total emissions are divided by the lifetime miles of the vehicle. This facilitates comparisons with ICEVs.

For each vehicle scenario, we evaluate a set of 2025 models with improved battery systems (Table 2). We then compare this to both current market BEVs, as well as a set of 2025 models with increased battery capacity and travel range (Long Range or LR). Vehicle scenarios are evaluated across a set of use-phase scenarios reflecting differences in travel behavior, vehicle life, and electricity generation. The model includes both the operation and non-operation stages of the vehicle life cycle.

The vehicle life cycle is divided in two phases; the vehicle phase, which includes vehicle production and disposal, and the operation phase. The vehicle phase is broken down into the battery system and the rest of the vehicle, referred to as the glider. The end-of-life (EOL) stage includes disposal and recycling of the glider. Disposal and/or recycling of the traction battery is not included because of uncertainty in how batteries will be managed in the future, particularly as many more batteries are retired and either recycling networks or second life uses emerge.

Use-phase emissions for BEVs are then estimated as a function of vehicle energy efficiency and the emissions associated with electricity production and delivery. Two sets of travel scenarios were applied to the different vehicle models shown in Table 2:

1. A privately-owned vehicle in an average US Household (referred to as the AVE scenario)
2. A service vehicle deployed in an urban, ride-hailing fleet (referred to as the SAV scenario)

To capture regional variability, changing fuel sources, generation technologies, and policy in the electricity system, a range of electricity generation forecasts were modelled for both California and the US region from the period 2017 to 2025. The electricity generation scenarios are discussed further in a later section.

2.2 LCI Inventory Model

The life cycle inventory (LCI) model tracks only energy consumption and GHG emissions. A three part LCI model was developed to estimate the required inputs of energy and raw materials and resulting emissions: part one evaluated the production of the vehicle glider body and balance of systems (the glider model); part two evaluated the production of the battery system; and part three evaluated the generation of electricity supplied to charge the vehicle.

Table 2: Overview of Vehicle Scenarios Included in this Study

	ICEV car	ICEV SUV	HEV car	2012 MY Leaf	2018 EOV	2018 PLS	2018 PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR EOV	2025 LR PLS	2025 LR PSUV
Fuel Economy (kWh/100 mi)	116	160	80	28.6	28.6	33.5	39.4	28.1	31.4	35.5	32.1	34.4	39.5
Battery Capacity (kWh)	-	-	-	24	60	100	100	60	100	100	100	125	175
Utilization (VMT) Scenarios (annual VMT in year 1 shown*)													
AVE	13467	14026	13467	12135	12135	12135	14026	12135	12135	14026	13467	13467	14026
SAV-High	-	-	-	-	-	-	-	-	-	-	69350	69350	69350

*VMT changes every year with a decreasing trend (NHTS, 2017)

2.2.1 Glider Model

The glider model examined the life cycle emissions of the vehicle without the battery, which included raw material acquisition and refining, processing, assembly and disposal. The reference LCI data for this model was acquired from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) 2 Model developed by Argonne National Laboratory (Argonne National Laboratory, 2017b). This data source provides the per-mass life cycle embodied energy and air pollutants, including GHGs, for materials used in vehicles. The data were combined with estimates of the material composition of vehicle gliders and their masses. The mass used for each modelled glider was the curb weight of the reference vehicle for each archetype (EOV/Chevy Bolt, PLS/Tesla Model S, PSUV/Tesla Model X) reduced by the mass of the battery. The impacts of material transformation were calculated for each material. The per-vehicle assembly and disposal impacts were assumed to be identical across all modelled BEVs. Other assumptions included the mass and number of replacements for fluids and tires, also acquired from the GREET 2 model. Further, because electricity use does not constitute a large portion of total energy use and resulting emissions in this phase, time dependence of the electric grid was not considered in the glider model–meaning that a vehicle produced in the future is modeled using the same electricity grid LCI as those produced today. For both 2018 and 2025 scenarios, glider material composition as well as per-mass emissions are assumed to be the same. And since no light-weighing was assumed, glider masses also remain the same. The baseline ICEV car, SUV, and HEV scenarios presented for comparison are taken from the default vehicle set in GREET 2. The resulting estimates for the material balance of the vehicles, the average energy input for assembly processes, and further details on the vehicle model can be found in the Supporting Information S3.

2.2.2 Battery Production

Battery production LCIs were developed using the model described in Ambrose and Kendall (2016), which combines the Battery Performance and Cost (BatPAC) model and underlying research from Argonne National Labs (Dunn et al.); Nelson et al. (2011) with life cycle inventories from GREET 2 to examine the GHG emissions and material composition of lithium-ion batteries (LIBs) for light-duty applications. The methods used to develop this model are described in Ambrose and Kendall (2016). All vehicle scenarios are assumed to use a lithium nickel manganese cobalt (NMC) battery chemistry. Variations of NMC have emerged as the dominate cathode chemistry for most light duty applications owing to its high specific power (Olivetti et al., 2017). The composition of lithium ion battery (LIB) packs can vary due to the type of cells used, thermal management systems, and structural elements. There is also considerable uncertainty in estimating the energy required for assembling LIB cells owing to limited, poor quality data (Peters et al., 2017). We considered several futures for battery design, production processes, and key inputs through a scenario based sensitivity analysis. These results, the normalized average material composition for each battery pack, assembly emissions estimates, as well as more discussion on the battery production model is included in the Supporting Information S4.

The baseline assumption is that no battery replacements are required over the course of a vehicle's lifetime. This assumption and the conditions where battery replacement is likely to be needed is discussed in Section 3.1.

2.3 Use-Phase Model

A use phase model was developed to estimate GHG emissions resulting from EV operation summarized in Equation 1, where the total emissions in kg CO_2-equivalent (CO_2e) for each technology (*i*) is the sum of, from 0 to the expected vehicle life (*n*), the annual miles travelled (*VMT*) in year (*t*), the average vehicle energy demands per mile (ρ_i), the LCGHG emissions rate for electricity generation in each year (*EF*), and the efficiency of the charger system (φ).

$$OperationsGHG_i = \sum_0^n VMT_{it} * \rho_i * {}^{EF_t}/_{\varphi} \qquad \text{Eq. (1)}$$

2.3.1 Vehicle Energy Demands

An existing vehicle dynamics model, the Future Automotive Systems Technology Simulator (FASTSim) tool developed and maintained by the National Renewable Energy Lab (NREL), was used to estimate the average vehicle energy demand (ρ_i). FASTSim simulates vehicle energy demands as a function of primary physical forces including drag, acceleration, ascent, rolling resistance, powertrain component efficiency and power limits, and regenerative braking (Brooker et al., 2015). Since FASTSim models vehicle performance at the powertrain component level, it allows users to modify the parameters of vehicle powertrain, such as battery capacity, energy density, motor power, glider dimensions, and weight to examine how powertrain design impacts fuel economy. The model was used to simulate vehicle energy demand. To ensure that this model represents vehicle performance appropriately, the model was parameterized for the 2012 and 2018 model years of the three archetypal vehicles and simulated results were validated against fuel economy values reported by the EPA (Environmental Protection Agency (EPA), 2018). FASTSim results were found to be within a 7% range of the EPA reported fuel economy values for all models.

Table 3: Vehicle mass and key parameters by scenario

	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR EOV	2025 LR PLS	2025 LR EOV
Drag coefficient	0.32	0.31	0.24	0.25	0.31	0.24	0.25	0.31	0.24	0.25
Frontal area (m^2)	2.76	2.82	2.34	2.59	2.82	2.34	2.59	2.82	2.34	2.59
Curb Weight (kg)	1557	1619	2215	2459	1448	1929	2173	1640	2050	2543
Battery mass (kg)	290	460	766	766	288	481	481	481	601	841

Table 3 shows the assumed curb weight and key vehicle specification inputs by vehicle scenario. The aerodynamic and motor specifications are held constant across each class of vehicle modeled. As explained in the section on Glider model, curb weights vary according to battery system improvements and battery sizing.

It is widely expected that recent developments in LIB technology will enable battery packs with nearly double the energy density of early EV batteries. Use of higher capacity cathodes, more efficient thermal management, improved electrolytes and anode materials could increase battery specific energy from today's ~130 Wh/kg to over 250 Wh/kg by 2022 (Elgowainy et al., 2016). The current (2018) vehicle scenarios assume an average battery density of 138 Wh/kg, while the 2025 scenarios assume an energy density of 208 Wh/kg, an improvement of 6% - 8% per year (US DRIVE 2013). Hence in the 2025 vehicle models, the expected increase in future battery density brings down the curb weights when battery capacities remain the same as 2018 vehicle models. But as battery capacities are increased in the long range scenarios, the curb weights increase accordingly. Additional review of the BEV assumptions and discussion is provided in the Supporting Information S5.

The ICEVs included in the study for comparison are drawn directly from GREET 2, and include both emissions from fuel production (i.e. WTP) and fuel combustion (i.e. PTW). The ICEV WTP and PTW emissions rates were estimated from the default ICE sedan, SUV, and HEV scenarios and VMT assumptions in GREET 2. The average fuel economies for these scenarios are 34 MPG for the sedan, 24 MPG for the SUV, and 42 MPG for the HEV respectively, while upstream emissions from fuel production as a share of combustion emissions (i.e. WTP/PTW) is 0.24 to 0.27.

2.3.2 Vehicle Miles Travelled (VMT)

Automotive LCAs commonly rely on an assumption of fixed or average lifetime mileage, often based on data from industry associations or anecdotal data (Weymar, 2016). In reality, the total miles travelled by the vehicle lifetime (*LifetimeVMT*) is driven by two phenomena (Eq. 2): one, the scrappage rate (*M*), which is the probability or fraction of a given model year's vehicles retired in each year (*t*) for each vehicle model year (*a*); and two, the utilization of the vehicle over the service life, defined here as the annual VMT (*AnnualVMT*). In the US, survival and annual VMT data suggest two important trends: one, differences in the rates of survival and mileage generation across vehicle types; and two, a strong decline in mileage generation over the life of the vehicle, with older vehicles generally less likely to experience high annual mileage (Lu, 2006).

$$LifetimeVMT_a = \sum_t \ (1 - M_{at}) * \ AnnualVMT_{at} \qquad \text{Eq. (2)}$$

Two vehicle utilization scenarios were considered: one representing primary use in a personal passenger vehicle application and another representing use in a shared on-demand or potentially automated ride-hailing fleet (a shared autonomous vehicle, or SAV). To estimate a function for annual mileage of personal vehicles, the average annual VMT for gasoline cars (i.e. automobiles and station wagons), HEVs, and gasoline SUVs (e.g. Santa Fe, Tahoe, Jeep, etc.) in the 2017 NHTS were regressed against vehicle age. The 2017 NHTS collected information on the type (e.g. car, van, SUV, or truck), fuel, hybrid or electric powertrain, and annual mileage of vehicles present in the household. While there are relatively few BEVs reflected in the 2017 NHTS sample (n=545 out of n=252,042 vehicles), BEVs reported 10% fewer annual miles travelled compared to ICEVs. Conversely, HEVs reported 19% more annual miles compared to ICEVs. Due to the limited data on BEV annual mileage, the annual mileage for gasoline cars and SUVs were scaled linearly by the average difference in the NHTS sample to estimate annual miles for BEV and HEV scenarios. The resulting linear functions and parameter estimates for annual mileage of the different vehicle types are provided in the Supporting Information Table S6.1.

US vehicle scrappage data from 1999 – 2009 were used to estimate the average lifetime of vehicles for car and SUV scenarios respectively (Jacobsen and Van Benthem, 2015). The lifetime annual mileage is then calculated as the cross product of the survivability and the annual VMT estimate (Lu, 2006). This results in an estimated lifetime mileage of 155,276 miles for cars, 161,890 for SUVs, and 184,752 miles for HEVs, and an average vehicle life of 12.6 years. Given the lower annual VMT for BEVs, the same historical survival data yields a lower estimate for lifetime mileage of BEVs; 139,914 lifetime miles for EOV/PLS scenarios, and 148,775 miles for the PSUV scenario. However, the cause for lower annual mileage is not known, and could, for example, reflect range restrictions that are not representative of future BEVs. Because of uncertainty in how future vehicle lifetimes may unfold, vehicle annual and lifetime mileage is examined using three scenarios. The first, or baseline, scenario (Mileage Scenario 1) reflects the method described in equation 2 and applying the linear scaling of annual mileage as described in table S6.1. The second scenario (Mileage Scenario 2) is identical to Mileage Scenario 1, except that it treats BEVs and their ICEV analogs as identical with respect to annual and total lifetime VMT, while HEVs are represented by their respective NHTS annual mileage estimates. The third scenario (Mileage Scenario 3) treats the length of the use phase as constant across all vehicle and powertrain types at 12 years, but the difference in expected annual miles among all the powertrains are included (i.e. BEVs travel less, and HEVs more, than ICEVs). Table S6.3 in the Supporting information describes the resulting lifetime mileage for these three scenarios for each vehicle type.

The SAV scenario was modelled based on secondary empirical data from ride hailing vehicles (Henao, 2017), and simulations of potential automated vehicle fleets (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Loeb et al., 2018). In the SAV scenario, vehicles are assumed to travel 200 miles per day in service, and to have a declining utilization factor (i.e. days in service per year) averaging 80% over the vehicle lifetime. The survival rate is based on the observed ages and model years of livery taxicabs (Bishop et al. 2016). It is common for conventional livery cabs to travel from 70 to 200 miles per ten-hour shift, and average 42,000 to 72,000 miles annually depending on whether they are privately owned or operated in a fleet (Schaller Consulting, 2006). Bishop et al. (2016), estimated that the age of taxi cabs varied between 5.5 and 8.3 years between 1997 and 2014, with over 17% of taxis in the Chicago area exceeding 10 years of age in 2014. These data also suggest that livery taxis could well exceed 500,000 lifetime miles, which is a colloquial target for the iconic black, FX4 Fairway taxis of London (Bobbitt, 2002). For the SAV scenario, the survival method yields an estimate of about 351,000 to 584,000 lifetime miles, with average vehicle service life between 5.4 and 9.1 years. In Mileage Scenarios 1, SAVs are expected to travel 583,564 miles. Additional information on d lifetime VMT for SAV scenarios is provided in the Supporting Information Table S6.3.

2.3.3 Charging

BEVs are likely to utilize a range of private or public charging infrastructures with different power levels for charging events, which could impact the efficiency of refueling the vehicle (Smart and Schey, 2012; Tal et al., 2014). Sears et al. (2014) collected data on charger efficiency for a range of charging power levels and climate conditions from a small sample of Nissan Leaf and Chevy Bolt drivers; the authors found efficiency ranged 83.8% to 89.4% for Level 1 vs 2 charging events. There are much more limited data is available for the efficiency of high power chargers. It is likely that any variability in BEV emissions rate attributable to variation across charging infrastructures is less than that due to climate, driving distance, and other factors (Taggart, 2017). In this study, an average efficiency of φ = 86% is used for all scenarios, and the sensitivity of results to this assumption is explored in the discussion.

2.3.4 Electricity Generation

LCAs of EVs have long struggled to determine how best to model electricity used in vehicle charging. The alternatives from a modeling perspective are typically framed as either a consequential perspective (how the additional or new demand from a BEV charging event is met) or an attributional perspective, where BEVs are treated as requiring an average unit of electricity. The average emissions or attributional approach assumes all electricity as a shared resource for all end uses, while the consequential emissions approach recognizes the role of certain generators in meeting marginal demand, thereby scaling in response to the incremental load of vehicle charging (Alexander, 2015b). Researchers have taken different approaches for estimating marginal emissions. Some studies try to identify the marginal electricity supply based on what will be or has been dispatched amongst the current mix of sources in response to an extra load, while other studies have looked at long term change in the grid mix in response to the additional demand from EVs (Archsmith et al.; Siler-Evans et al., 2012). While there is a strong argument for consequential approaches to estimating electricity emissions, the focus of this study is not to capture the short term consequences of deploying electric vehicles. Instead, the goal is to estimate how trends in the foreground system (i.e. vehicle production and use) and background system (e.g. electricity grid mix) are likely to change the LCGHG performance of future vehicles. As such, the average fuel mix and associated GHG emission factors are used to estimate vehicle operation emissions for each year of vehicle operation.

The projected electricity generation by fuel source was obtained from the US Energy Information Administration (2018). Two regions were considered, the California sub region of the Western Electricity Coordinating Council region (CAMX), and the U.S, national average. The California scenario provides a useful comparison: California represents nearly 50% of the US BEV fleet, over 8% of new vehicles sold in the state are electric (compared with 2% nationally), a large share of electricity in California is generated by renewable sources, and finally, the state has enacted progressive policies pushing further deployments of renewables and EVs (Argonne, 2019). For both regions, emissions were evaluated under a reference case or business as usual scenario (BAU), and a carbon tax scenario which assumes a $25 allowance fee on CO_2 emissions from utility-scale electricity generators beginning at $25 (in 2017 dollars) in 2020 and increasing at 5% per year in real dollar terms (US Energy Information Administration, 2018). The carbon tax scenarios were included to represent the potential impact of further changes to the grid mix, particularly for in-use vehicles, and the magnitude of potential change for the average US fleet. The average emissions rate (EF_t) is estimated as the mass of GHG equivalent emissions per unit of delivered energy with Equation 3, where the weighted generation by year (*t)* and fuel source (*x)* is multiplied by the life cycle inventories (*LCI)* of emissions species (*e)* by fuel type (*x*), and the impact characterization factors (*m):*

$$EF_t = \frac{Fuel_{tx}}{\sum_x Fuel_{tx}} * LCI_{xe} * m_e \qquad \text{Eq. (3)}$$

The resource mix was broken into five fuel source categories: coal, natural gas, renewables, nuclear, and fuel oil. Generator technology LCI data were drawn from the 2017 GREET 1 model (Argonne National Laboratory, 2017a), and a representative LCI was estimated for each fuel source based on the net generation by generator type for each regional scenario (US Environmental Protection Agency, 2016). The renewables were treated as zero emission fuels here. The resulting carbon intensity forecasts for each electricity generation mix are shown in Figure 2(B), and the full results are available in the supporting information (S7).

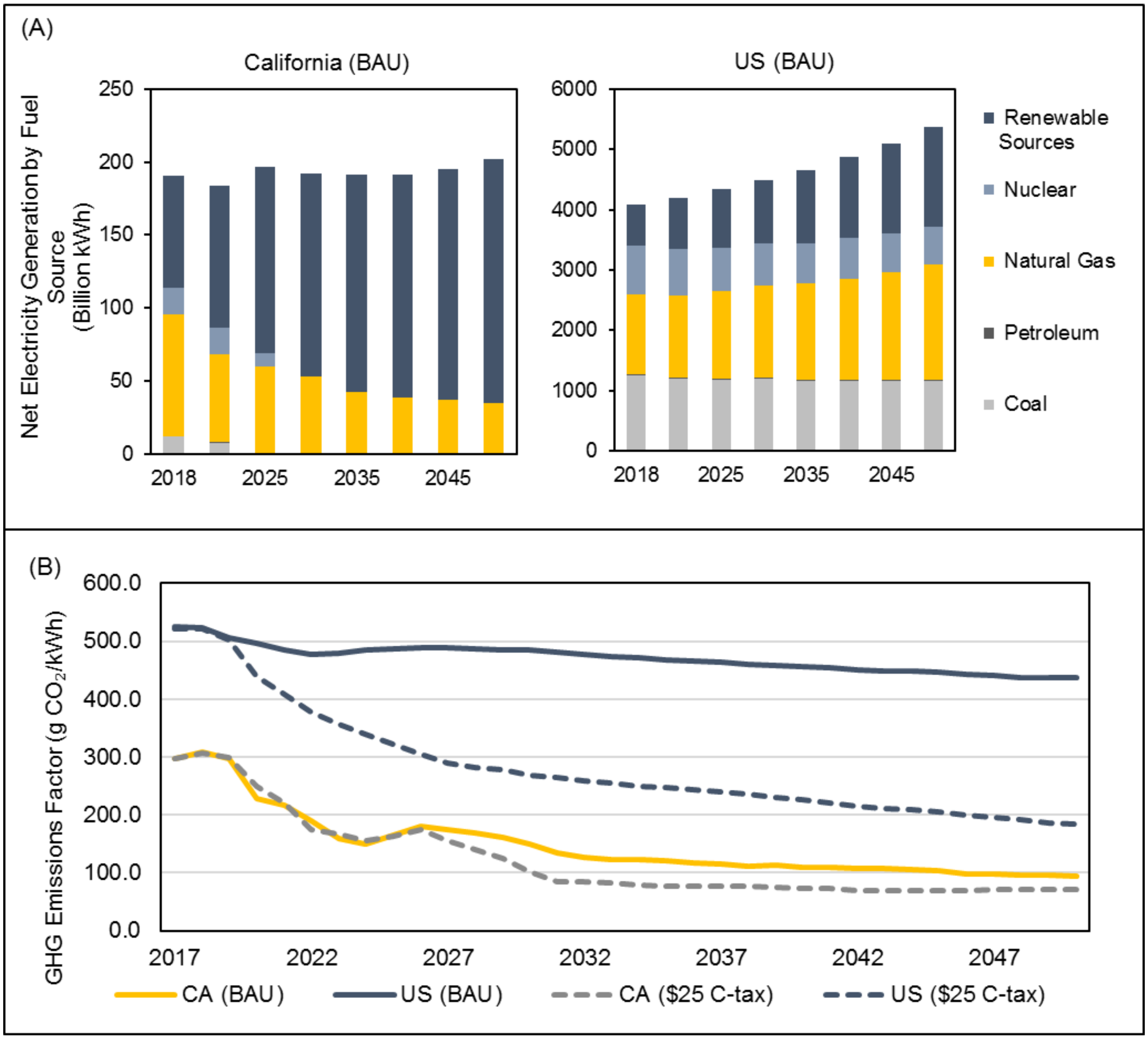

Figure 2 (A) Total Electricity Generation by Fuel Source in California and the US and (B) Average GHG Emissions per kWh for Residential and Commercial End-Uses for BAU and $25 carbon tax ($25 C-tax) scenarios in California and the US (2017 – 2050)

3 Results

LCGHG emissions for current market BEVs were found to range from 136 gCO_2e/mile for an efficiency-oriented compact BEV in California up to 324 gCO_2e/mile for the larger PSUV in the US average scenario. LCGHG emissions for 2025 BEVs decrease to 105 gCO_2e/mile for an efficiency-oriented compact BEV in California, while potentially increasing to 374 gCO_2e/mile for the larger PSUV in the US average scenario. This compares to conventional ICEV life cycle emissions of 460 to 504 gCO_2e/mile and to HEV life cycle emissions of 301 gCO_2e/mile. Figure 3 summarizes the average contribution of vehicle and battery production, vehicle end of life, and vehicle operation to life cycle GHG emissions for each vehicle and utilization scenario based on Mileage Scenario 1. Life cycle emissions from (non-SAV) BEVs under the California scenarios (121 to 205 gCO_2e/mile – blue diamonds in Figure 3), were ~45% lower than under the US average scenario (219 – 374 gCO_2e/mile). Across all the three vehicle archetypes, emissions for the long range (LR) vehicles increased by 17% - 30% for 2025 models. Like ICEVs and HEVs, the main driver of LCGHG emissions for BEVs is frequently the operation phase. But, while only 8% to 12% of LCGHG emissions for ICEVs are attributable to vehicle production, production emissions were estimated to contribute 30% - 66% of per mile emissions for BEVs. Production of the battery system contributed 28% - 51% of vehicle production emissions for BEVs, and 11% to 35% of overall per mile emissions.

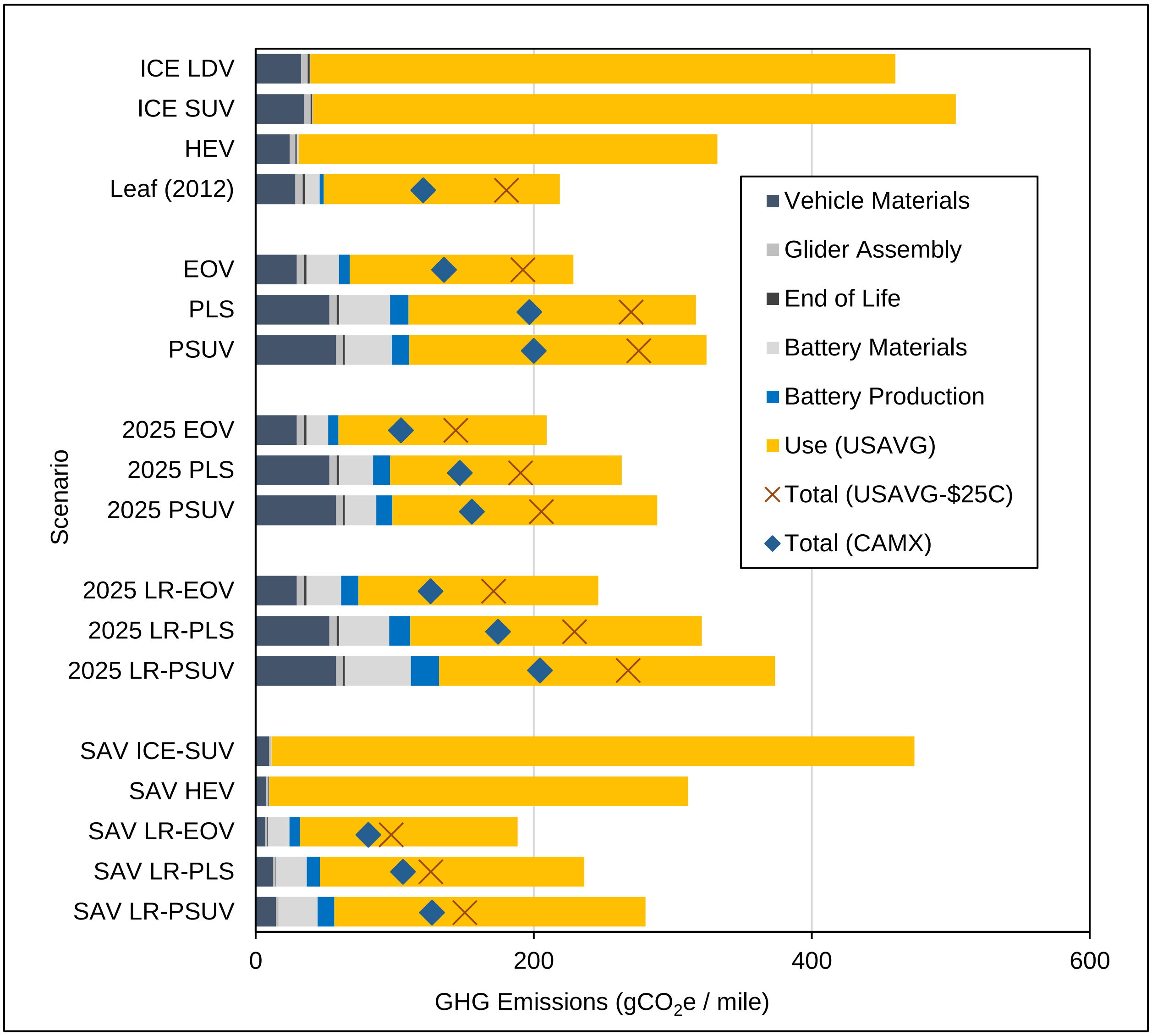

Figure 3 LCGHG Emissions of vehicle, battery, and use phase by vehicle, grid, and utilization scenario, assuming Mileage Scenario 1

Figure 3 reflects the mileage and vehicle lifetime assumptions represented by Mileage Scenario 1. Mileage Scenario 2 resulted a 2-7 gCO_2e/mile reduction in LCGHG emissions for BEVs (130 to 367 gCO_2e/mile), due to higher total lifetime mileage, which led to a lower contribution from vehicle and battery production on a per-mile basis as well as more vehicle miles accumulated with lower LCGHG intensity electricity. Mileage Scenario 3, in which vehicle lifetime is fixed at 12 years for all vehicles, resulted in less than a ±1% change in all non-SAV applications, as shown in Table S8.1 of the Supporting Information.

The $25 US carbon tax scenario reduced life cycle emissions of current (2018) BEVs by 12% - 15% compared to the USAVG (red × – Figure 3); emissions reductions grew to 23% - 38% for 2025 BEV models. The carbon tax scenarios reveal the importance of assumptions about electricity generation over time in estimating use phase emissions rates and the significance of use-phase emissions in life cycle emissions. This includes both the types of generation technologies and fuel sources associated with electricity for vehicle charging. While BEV emissions were lower under the carbon tax scenarios, the difference was significantly larger for the US case (Table S8.2 of the Supporting Information).

The SAV scenarios assume the 2025 LR vehicle archetypes and grid mix, and these vehicles are assumed to travel approximately 200 miles per day, for an average of 5.45 times the annual mileage of the personal SUV scenario. The SAV scenarios resulted in lower LCGHG emissions for BEVs on a per mile basis compared to the private average personal vehicle scenarios when compared over equivalent service periods. The use of BEVs could reduce LCGHG emissions of service vehicles by over 44% when switching from a comparable ICEV PSUV and 42% when switching from a comparable HEV to a 2025 LR-EOV. These reductions become more significant under the carbon tax scenarios, with the BEV SAVs averaging 57 – 86 gCO_2e/mile under the California with $25 carbon tax scenario.

In these high mileage applications, it is also expected that key vehicle systems will require additional replacement due to excessive wear. The results reported for the SAV scenarios assume replacement of vehicle battery based on expected lifetimes. Battery systems are assumed to be replaced after delivering a fixed number of equivalent charge and discharge cycles, and the estimates in Figure 3 for BEV SAVs assume an average 1 to 1.5 battery replacements over the average 12 year vehicle life. Vehicle powertrain, chassis, and other systems were not assumed to experience additional replacements as a function of mileage. An expanded results section, including a full accounting of results from the carbon tax and SAV scenarios is include in the supporting information (S8). The service life of the battery is discussed further in the next section.

3.1 Battery Replacement and Vehicle Lifetimes

Battery cycle life is generally defined by the total number of times a battery can deliver its energy storage potential in a particular discharge program (Barré et al., 2014; Fortenbacher et al., 2014; Han et al., 2014), thus the service life will vary under different duty cycles and operating conditions. The effective cycle life is highly dependent on the utilization of storage potential and the rate of discharge. A common metric or measurement of battery performance is cycles to 80% depth of discharge (DOD), or 80% of the battery energy storage potential. Cycles to 80% DOD is also convenient as utilization of the battery near the maximum and minimum of the battery potential are associated with accelerated battery degradation. Many battery systems are managed to prevent discharge below or charging above a certain threshold to prevent damage to the battery system. While early lithium ion cells might only deliver several hundred cycles before experiencing noticeable capacity degredation (>20%), current and future batteries are expected to exceed 1000 cycles and may reach 5000 to 6000 cycles at 80% DOD (Burke, 2014; Howell et al., 2018).

Given the average vehicle miles traveled (VMT) of personal vehicles and the range of vehicles included in the study, batteries would not necessarily exceed 1000 equivalent cycles over the average vehicle lifetime (12 years). Figure 4 shows the cumulative average battery cycles to 80% DOD for each scenario considered in this study. The vehicle survivability rates for cars and taxis are also included to illustrate the percentage of vehicles expected to still be in service by year. In ride hailing applications, recent literature suggest vehicles could travel more than 2 to 5 times the average daily vehicle miles of a comparable personal vehicle (Fagnant and Kockelman, 2014; Gurumurthy and Kockelman, 2018; Henao, 2017). In the SAV scenarios, where vehicles travelled 200 miles per day on average, battery replacement could be required over the vehicle lifetime to ensure that older vehicles continue to meet range requirements. In the SAV scenario, battery systems are discharged completely on most days and experience 277 - 323 equivalent cycles per year (Figure 4). Assuming a limit of 1500 cycles to 80% DOD, the average vehicle would require one battery replacement on average (0.8 to 1.5 replacements in 12 years depending on battery size).

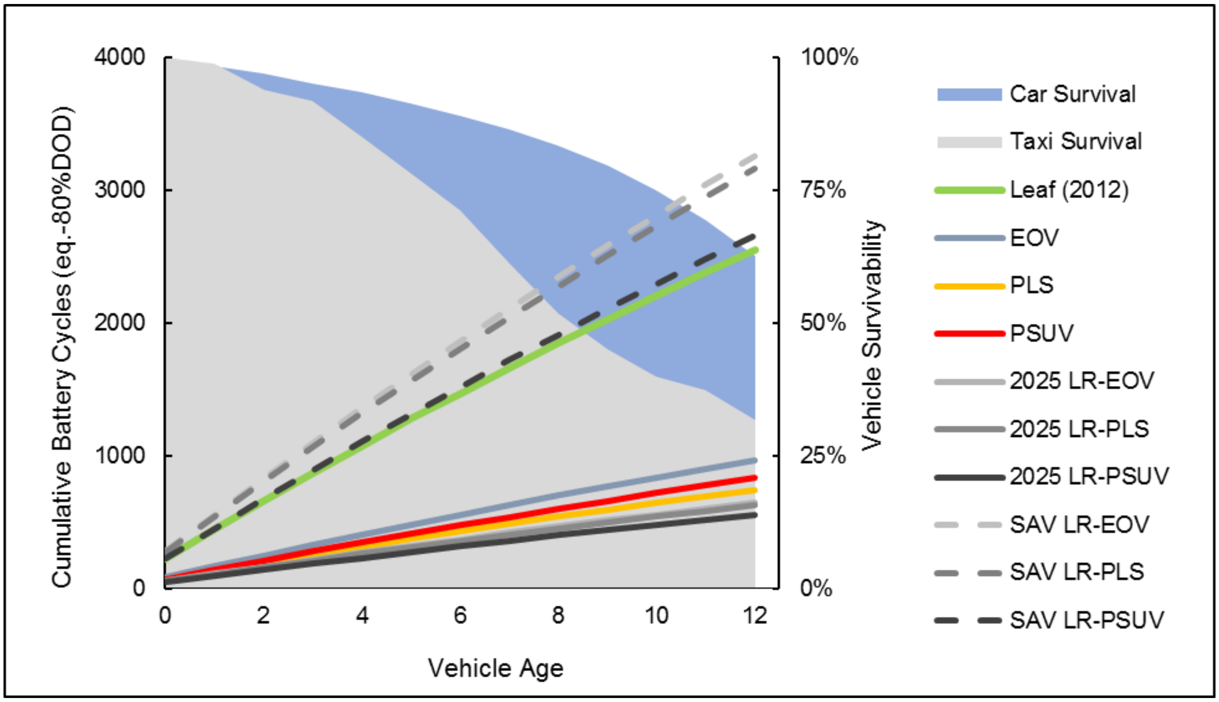

Figure 4 Battery Cycles and Vehicle Survival by VMT Scenario

3.2 Electricity

Emissions generated during the vehicle use-phase from producing electricity to charge the vehicle are on average more than 50% of LCGHG emissions. A key uncertainty in estimating use-phase emissions for BEVs stems from variability in the emissions rate for delivered electricity. The effects of BEV efficiency on per mile emissions have also been poorly addressed in many previous studies due to the limited types of vehicles evaluated. Figure 5 shows the relationship between vehicle efficiency (kWh/100 miles) vs. the GHG emissions per kWh of energy for vehicle charging. The labelled lines are constant emissions rates delimitating ranges of emissions from 100 to 500 gCO_2e/mile. The average life cycle emissions rate for current and 2025 LR vehicle archetypes are also indicated in the California and US reference case (BAU) grid scenarios in the left and right panels respectively.

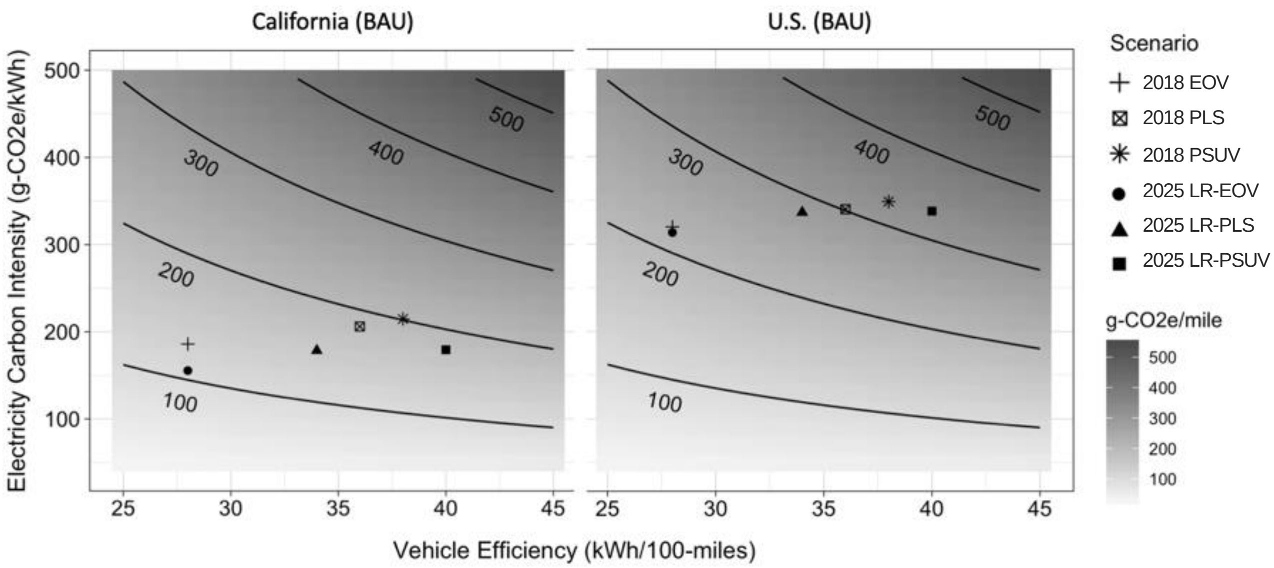

Figure 5 EV LCGHG Emissions per Mile with Sensitivity to Grid Emissions and Vehicle Efficiency

4. Discussion

Increasing BEV battery capacities could have mixed impacts on the life cycle emissions rate of grid-tied BEVs and the GHG abatement from a transition away from gasoline-powered vehicles. Longer range BEVs could reduce barriers to adopting electric vehicles and enable more electric vehicle travel where charging infrastructure is undeveloped, but the materials and energy required to manufacture batteries could have a significant contribution to per-mile emissions rates, particularly when vehicles have low utilization. In the absence of other measures to de-carbonization electricity for charging vehicles, future longer range BEVs may have higher life cycle emissions rates than current BEVs.

A shift towards larger, less efficient vehicles can offset current transportation emissions abatement measures, but would only increase the importance of vehicle electrification to goals for de-carbonization. The 2017 NHTS data used in this study suggest SUVs and larger passenger vehicles travel 8% more miles per year on average, but this discrepancy is skewed towards older vehicles. Older SUVs can travel 20% more miles than the comparable age US passenger car. Prior assessment by the EPA for the mid-term evaluation for the Corporate Average Fuel Economy Standard found a similar pattern of vehicle aging on annual vehicle miles travelled for cars and light trucks (US Department of Transportation, 2017). While larger BEVs could have twice the emissions rate of efficiency-oriented compact designs, the total reduction in emissions of switching from an ICE SUV to a BEV SUV is equivalent or greater to that for cars. This highlights the increased benefit of substituting electric powertrains for gasoline powertrains in large, less efficient vehicles and the potential benefits of EVs entering that market segment.

The fuel efficiency of ICEVs are also expected to improve by 2025, which could impact the relative benefits of electrification. Under the rules adopted in 2017 for vehicle GHG emissions and fuel efficiency targets for the Corporate Average Fuel Economy (CAFE) standards, the average fuel efficiency of light duty vehicles was expected to increase by 35% from 2018 to 2025, resulting in approximately a 20% decrease in LCGHG emissions per mile. In 2019, the National Highway Traffic Safety Administration (NHTSA) and EPA have proposed the "Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021– 2026 Passenger Cars and Light Trucks". The preferred alternative under SAFE would maintain the 2020 model year standards for CAFE and tailpipe carbon dioxide emissions for passenger cars and light trucks through 2026, effectively freezing the standard and reducing regulatory motivation for improved fuel efficiency.

In general, BEVs in the US have 35% - 50% lower LCGHG emissions per mile than current, comparable ICEVs. The magnitude of emissions reductions from BEV adoption are in large part determined by how electricity for vehicle charging is generated. The time of day, day of the week, time of year, and power level of charging events all impact the emissions rates of electric vehicles, which signals towards the opportunities for improving BEV LCGHG emissions through optimizing charging strategies (Hoehne & Chester, 2016). The carbon tax scenarios reveal the significant potential reductions in BEV emissions rates with relatively modest increases in renewable generation. The minimum BEV emissions rate under the California + $25 carbon tax scenario was 108 gCO_2e/mile for the EOV. While this represents a 75% reduction from the current ICEV, it would be insufficient to meet the state's climate policy target of climate neutrality by 2045 given expected levels of VMT generation (Executive Order B-55-18).

Extending the vehicle life of BEVs and increasing vehicle utilization can lower the LCGHG emission intensity (i.e. gCO_2e/mile) rate of BEVs. BEVs in high-mileage applications such as ride-hailing were found to have lower LCGHG emissions despite the potential for additional battery replacement. This was attributable to increased utilization of battery and vehicle systems (vehicles are usually idle), and the decreasing carbon intensity of electricity emissions.

There are some important limitations or caveats with respect to what we can learn or understand from this work. In particular, rapid changes in technology performance or the emergence of new and unanticipated technologies or vehicle use models are not addressed in this work. Instead, we examined trends in BEVs, as we understand them today, and extend them into the future. In addition, ICEV technologies were treated as static, meaning that improvements in ICEV technologies and fuels were not considered.

5. Conclusions

This study examined trends in BEV design choices and use models including battery pack size, vehicle archetype, and vehicle utilization (annual VMT assumptions), as well as changing electricity emissions to examine the potential effects on LCGHG emissions of BEVs. While BEVs can reduce emissions relative to conventional ICEVs, trends in vehicle choice, utilization of increasing battery capacity, and considerations of future ownership and utilization models all influence their relative performance. In particular, the trend towards larger vehicles with larger battery packs leads to a deterioration in BEV GHG mitigation potential compared to ICEVs as a result of both vehicle production and operation emissions. At the same time, the decreasing carbon intensity of electricity grids over time, not to mention current and future differences over space (i.e. California versus US average grid emissions), are largely countervailing trends that lead to improving GHG mitigation potential for BEVs over time. Increasing battery capacity (i.e. larger batteries), can reduce the per-mile life cycle emissions for vehicles, however, if they enable high-mileage use models, such as vehicles used in ride-hailing applications.

These results suggest three important conclusions: (1) like all vehicle types (whether ICEVs or BEVs) larger high-performance vehicle choices are likely to decrease energy efficiency and thus increase emissions; (2) the most benefit for investing in large-capacity batteries and BEVs more generally are in high-mileage applications; and (3) including trends in BEV design choices, temporal and spatial heterogeneity of electricity grids, and new vehicle use and ownership models lead to non-negligible differences in estimates of the LCGHG emissions (and mitigation potential relative to ICEVs) of BEVs. The results highlight predictable opportunities to increase the abatement potential of BEVs, such as de-carbonization of the electricity grid and a focus on vehicle energy economy. Slightly less obvious opportunities include right sizing batteries based on expected vehicle use, or put differently, higher utilization rates for BEVs (especially those with larger battery capacity).

Acknowledgements This research was supported by a grant from ITS Davis's Sustainable Transportation Energy Pathways (STEPS) Program entitled *LCA of light duty Electric Vehicles – examining trends in vehicle efficiency, performance and battery capacity*.

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SUPPORTING Materials for:

Ambrose, H., Kendall, A., Wachche, S., Lozano, M., Fulton, L., Trends in Life Cycle Greenhouse Gas Emissions of Future Light Duty Electric Vehicles. *Transportation Research Part D: Transportation and the Environment*

These supporting material (SM) provides summary tables used to generate all figures in the main text. The SM also contains sections with additional calculations and data as described in the main text. The SM is organized as follows:

Section S1. Literature survey for Life Cycle GHG Emissions from Battery Electric (BEV), Internal Combustion Engine (ICEV) and Hybrid Electric Vehicles (HEVs)

Table 1 in the main text summarizes some of the key findings of prior studies examining the life cycle greenhouse gas (GHG) emissions of light duty vehicles, and provides comparison with both pure gasoline vehicles with a hybrid electric powertrain, and conventional gasoline ICEVs. Table S1.1 provides a full list of the studies included, referenced, or used for calculations in Table 1.

Table S1.1 Summary of Studies Examining the Life Cycle GHG Emissions of BEVs, ICEVs, and HEVs (Archsmith et al., 2015; Bandivadekar, 2008; Burnham et al., 2006; Dunn et al., 2012; Ellingsen et al., 2014; Graff Zivin et al., 2014; Hawkins et al., 2013; Kendall and Price, 2012; Kim et al., 2016; MacLean and Lave, 2003; Majeau-Bettez et al., 2011; Mercedes, 2008; Miotti et al., 2016; Notter et al., 2010; Samaras and Meisterling, 2008; Tamayao et al., 2015)

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle + Battery Production (kg CO_2e)	Battery Production (g CO_2e/km)	Vehicle + Battery Production (g CO_2e/km)	Vehicle Operation (g CO_2e/km)
Samaras and Meisterling (2008)	PHEV	20.1	7903	10	41	40
Notter et al. (2010)	BEV	34.2	6253	7	32	101
Majeau-Bettez et al. (2011)	BEV	24	7396	19	48	
Dunn et al. (2012)	BEV	28	7039	4	32	
Hawkins et al. (2013)	BEV	24	7934	18	50	
Ellingsen et al. (2014)	BEV	26.6		26	26	
Graff Zivin et al. (2014)	BEV	24				69 - 293
Miotti et al. (2016)	BEV	19 - 60	7389	4	34	120 - 185
Tamayao et al. (2015)	BEV	24	2616			41 - 144
Kim et al. (2016)	BEV	24	7640	14	44	
Archsmith et al. (2016)	BEV	28	7765	6	37	124 - 194
Maclean and Lave (2003)	ICEV		9600		38	285
Samaras and Meisterling (2008)	ICEV		8500		34	
Burnham et al. (2006), in Hawkins et al. (2012)	ICEV		7600		30	
Burnham et al. (2006), in Hawkins et al. (2012)	ICEV		7000		28	
Notter et al. (2010)	ICEV		6370		25	121
Hawkins et al. (2013)	ICEV		6566		26	
Miotti et al. (2016)	ICEV		8178		33	282
Archsmith et al. (2016)	ICEV		7207		29	248

Study	Vehicle Type	Battery Capacity (kWh)	Vehicle + Battery Production (kg CO_2e)	Battery Production (g CO_2e/km)	Vehicle + Battery Production (g CO_2e/km)	Vehicle Operation (g CO_2e/km)
Kim et al. (2016)	ICEV		6200		25	
Kim et al. (2016)	ICEV		7200		29	
Kim et al. (2016)	ICEV		7000		28	
Kim et al. (2016)	ICEV		7500		30	
Burnham et al. (2006), in Hawkins et al. (2012)	HEV		9200		46	
Bandivadekar (2008)	HEV		10800		54	
Samaras and Meisterling (2008)	HEV		8800		44	
Mercedes (2008), in Hawkins et al. (2012)	HEV		10600		53	
Kendall and Price (2012)	HEV		9900		40	139
Kendall and Price (2012)	HEV		17300		69	131
Miotti et al. (2016)	HEV		9200		46	242

Section S2. Battery Electric Vehicle Sales in the US

Table S2.1 summarizes the monthly sales data used to create Figure 1 in the main text. The monthly vehicle sales data was obtained from the Inside EVs Monthly Sales Scorecard (Loveday, 2019). The estimated average vehicle battery pack capacity was obtained from the EPA vehicle fuel economy data file.

Table S2.1

Model	Average Battery Pack Capacity	2012	2013	2014	2015	2016	2017	2018
BMW I3 BEV	33	0	0	6092	11024	7625	6276	6119
FIAT 500e	24	0	260	5132	6194	5330	5380	2740
Ford Focus	33.5	683	1738	1964	1582	901	1817	558
Chevrolet Bolt EV	60	0	0	0	0	579	23297	16674
Honda Clarity BEV	25.5	0	0	0	0	0	1121	1133
Hyundai IONIQ EV	28	0	0	0	0	0	432	204
Kia Soul Electric	30	0	0	359	1015	1728	2157	1113
Mercedes B250e	28	0	0	774	1906	632	744	89
Mercedes Smart fortwo ED	17.6	137	923	2594	1387	657	544	467
Mitsubishi i-MiEV	16	588	1029	196	115	94	6	0
Nissan LEAF	24	9819	22610	30200	17269	14006	11230	13388
Tesla Model 3	75	0	0	0	0	0	1772	131382
Tesla Model S	85	2171	19000	17800	25202	28896	27060	22445
Tesla Model X	100	0	0	0	214	18223	21315	19150
Volkswagen e-Golf	24.2	0	0	357	4232	3937	3534	1026

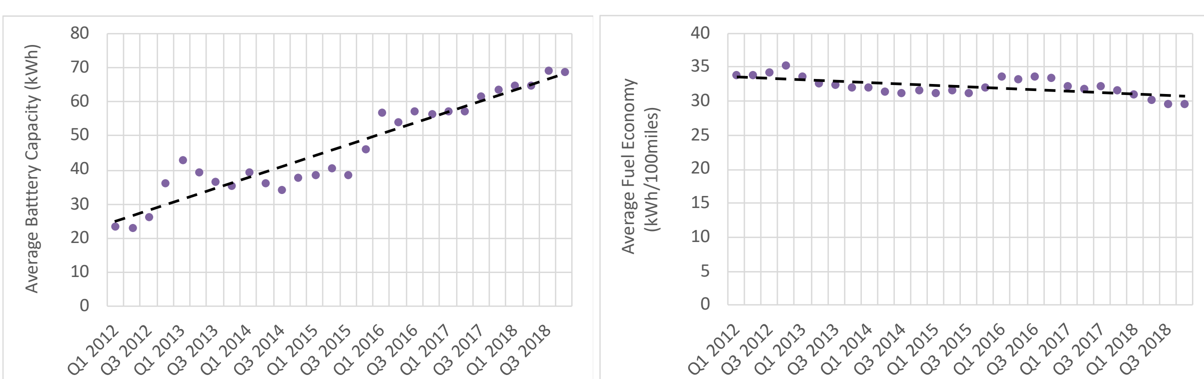

Figure S2.1 Average, Sales-Weighted Battery Capacity (Left) and Fuel Economy (Right)

Section S3. Vehicle Production

To model the emissions of the glider production, the material composition of the glider and its mass along with life cycle inventory of those materials is required:.

The life cycle inventory used to model LCGHG emissions associated with vehicle production, assembly, and disposal was acquired from the GREET 2 model (Argonne National Laboratory, 2017a). Their data on material acquisition and transformation, vehicle assembly, and vehicle disposal was combined with glider mass and composition to estimate emissions. In this study, the battery system was modelled separately from the rest of the vehicle, referred to as the glider. Hence the glider mass is calculated by subtracting battery mass from the curb weight. The material compositions for the Leaf (2012), PLS and the PSUV vehicle scenarios are based on material composition used in a similar study (UCS 2015) which builds off of material data used in GREET 2 model. The material composition for the EOV scenario is from the vehicle teardown performed on Chevrolet Bolt by Munro associates.

The material composition of the glider and mass used for each of the four modeled vehicle scenarios can be seen in Table S3.1.

Table S3.1 Average Glider Composition and Mass by Vehicle Group

	EOV	**PLS**	**PSUV**	**Leaf (2012)**
Steel	54.25%	21.0%	21.0%	66.0%
Cast Iron	4.24%	3.0%	3.0%	2.0%
Wrought Aluminum	2.12%	26.0%	26.0%	1.5%
Cast Aluminum	8.50%	17.0%	17.0%	5.0%
Copper/Brass	7.63%	6.0%	6.0%	5.5%
Glass	4.24%	4.0%	4.0%	3.0%
Average Plastic	13.56%	15.0%	15.0%	12.0%
Rubber	2.54%	2.6%	2.6%	2.0%
Glass Fiber-Reinforced Plastic	0.00%	2.5%	2.5%	0.0%
Others	3.0%	2.9%	2.9%	3.0%
Glider Mass (lbs)	2,609	3,505	4,043	2,785

Additional considerations included material transformation, fluid use, assembly, and disposal, which were also acquired from GREET 2 model. Fluids are included in the body and powertrain material life cycle stage of this study's model, and in EVs include brake fluids, powertrain coolant, and windshield fluid; sedans and SUVs were assigned different sets of lifetime fluid use, with the latter having higher fluids use. All vehicles were given identical assembly and disposal impacts, where the energy use was 11.57 mmBTU and 3.26 mmBTU respectively. Note that the modeled emissions may underestimate true impacts, as the life cycle emissions of the approximately 3% of “other” materials was not accounted for. Additionally, since electricity does not play a major role in this phase, time dependence of the electric grid was not included.

Section S4. Battery Production

The battery production model examined the cradle to gate of the battery life cycle, which included emissions from raw material extraction and refining, production, and assembly. An existing tool, the Battery Performance and Cost Model (BatPaC) constructed by Argonne National Laboratory, was used as the basis for the battery production model. BatPaC is based on a robust study of the material properties of LIB electrode and packaging materials, as well as battery pack design and production. BatPaC estimates the cost and composition of the LIB pack systems; in prior work (Ambrose, 2016), we connected these these outputs to material life cycle inventory data to estimate the GHG intensity of battery production processes. BatPaC offers the capabilities to compare the performance of different LIB cathode materials, however nickel rich cathode compounds NMC (e.g. 622 and 811), are being predicted to dominate light duty automotive applications (Curry, 2017). Table S4.1 summarizes the key parametric assumptions relating to the battery pack design, i.e. pack size, mass, power output, and cell and module capacity. The scenarios were developed based publicly available data on current models of archetypal vehicles described in main text.

Table S4.1 Battery Pack Configuration Detail

	Leaf	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV
Pack Capacity (kWh)	24	60	100	100	60	100	100	100	125	175
Pack Mass (kg)	295	434	723	723	288	481	481	481	601	841
Battery power, kW	100	170	386	568	170	386	568	170	386	568
Battery energy kWh	24	60	100	100	60	100	100	100	125	175
Number of cells per module	8	29	516	516	29	516	516	48	648	906
Number of cells in parallel	2	3	6	6	3	6	6	3	6	6
Number of modules in row	24	2	2	2	2	2	2	2	2	2
Number of rows of modules per pack	2	5	8	8	5	8	8	5	8	8
Number of modules in parallel	1	1	1	1	1	1	1	1	1	1
Battery Cathode Chemistry	LMO	NMC	NMC	NMC	NMC	NMC	NMC	NMC	NMC	NMC

The resulting breakdown of key materials are summarized in Table S4.2. Material LCIs were then obtained from the GREET 2018 model, and used to estimate the total energy and global warming potential for battery material production (measured in CO2 equivalents, or GHGs). We also conducted a sensitivity analysis on assumptions about battery assembly energy requirements (as measured by the kWh of energy input per kWh of usable storage) and pack energy density for the future vehicle case (Table S4.3). .

Table S4.2 Battery Material Composition by Scenario

	Leaf	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV
Aluminum (%)	32%	22%	32%	33%	22%	32%	33%	28%	24%	24%
Graphite (%)	12%	20%	14%	13%	20%	14%	13%	27%	12%	12%
PVDF (%)	2%	2%	2%	1%	2%	2%	1%	3%	1%	1%
Binder (%)	2%	2%	2%	1%	2%	2%	1%	3%	1%	1%
Copper (%)	11%	12%	17%	20%	12%	17%	20%	4%	6%	6%
Electrolyte (%)	2%	11%	9%	9%	11%	9%	9%	5%	34%	34%
Steel (%)	9%	3%	0%	0%	3%	0%	0%	2%	4%	4%
Coolant (%)	0%	1%	4%	3%	1%	4%	3%	2%	4%	4%
Plastics	2%	2%	2%	3%	2%	2%	3%	3%	2%	2%
BMS	1%	0%	1%	1%	0%	1%	1%	0%	1%	1%
Cathode Active Material (%)	27%	24%	17%	15%	24%	17%	15%	23%	11%	11%

Table S4.3 shows the results of the scenario based sensitivity analysis of battery production energy and GHG emissions. Under the high assembly energy scenario, total energy requirements and GHG emissions more than doubled. While the efficiency of production processes increases significantly, those gains are not sufficient to offset the increases in battery capacity.

Table S4.3 Battery Scenarios Sensitivity Analysis for 2025

	Leaf	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV
Assembly Energy Low (kWh)	804	2,118	3,530	3,530	2,118	3,530	3,530	3,530	4,413	6,178
Assembly Energy High (100 kWh/kWh)	2,374	5,904	9,876	9,912	5,904	9,876	9,912	9,801	12,305	17,229
Assembly Low GHGs (kg)	420	1,108	1,847	1,847	1,033	1,722	1,722	1,722	2,152	3,013
Assembly High GHGs (kg)	1,242	3,089	5,167	5,186	2,879	4,816	4,834	4,780	6,001	8,402
Material GHGs	1,481	3,080	5,133	5,133	2,048	3,414	3,414	3,381	4,226	5,916

Energy inputs and GHG emissions from battery assembly are primarily attributable to environmental controls and formation cycling. We assumed a constant inventory for battery assembly energy based on electricity generation for industrial purposes in South Korea. If the primary energy source for battery assembly was changed, this could significantly impact the emissions attributable to battery assembly energy inputs.

Section S5. Vehicle Energy Demands

FASTSim is a system analysis tool by NREL to compare the drivetrain performance. The model was first verified by modifying the inputs for three vehicles of our focus and cross checking the resulting fuel economy values with the 2018 values reported by the EPA. The vehicle parameter inputs are provided in Table S5.1

Table S5.1 Vehicle Input Parameters for FASTSim

	2018				2025			2025 LR		
	PLS	**PSUV**	**EOV**	**Leaf (2012)**	**PLS**	**PSUV**	**EOV**	**PLS**	**PSUV**	**EOV**
Drag coefficient	0.24	0.25	0.308	0.315	0.24	0.25	0.308	0.24	0.25	0.308
Frontal area (m^2)	2.341	2.59	2.816	2.755	2.341	2.59	2.816	2.341	2.59	2.816
Curb weight (lbs) input to fastsim	4883	5421	3570	3433	4254	4792	3192	4784	5851	3616
Curb (kg)	2215	2459	1619	1557	1929	2173	1448	2170	2654	1640
Vehicle glider mass (kg)	510	723	503	763	630	844	575	535	652	498
Battery mass	766	766	460	290	481	481	288	601	841	481
Motor power (kW)	285	311	60	80	285	311	60	285	311	60
Battery power (kW)	300	327	160	86	300	327	160	325	350	200
Battery energy (kWh)	100	100	60	24	100	100	60	125	175	100

Section S6. Annual Vehicle Miles Travelled (VMT)

Two sets of scenarios for vehicle travel were developed: one, representing primary use in a personal passenger vehicle application (US Department of Transportation).; and two, representing use in a shared on-demand or potentially automated ride-hailing fleet. In all scenarios, annual VMT decreases as the vehicles age due to a variety of factors. Table S6.1 shows the estimated annual mileage function for each scenario obtained from the regression of annual VMT on vehicle age within the NHTS data.

Table S6.1 Estimated Annual VMT Function from NHTS and Lifetime Miles by Vehicle Scenario

	Initial Annual Miles	Annual Reduction	Regression R^2
ICE Car	13604	-288.35	0.9219
ICE SUV	14152	-252.23	0.8579
HEV	16186	-343.07	0.9119
EV Car	12258	-259.82	
EV SUV	12752	-227.28	

The lifetime vehicle miles travelled presented in Table S6.1 were estimated using the survivability data for cars, SUVs, and taxis obtained from Jacobsen et al. (2015), and Bishop et al. (2016) respectively. Table S6.2 summarizes the survivability data used.

Table S6.2 Vehicle Survivability for Cars, SUVs, and Taxis

Vehicle Age	Car Survivability (Jacobsen, 2015)	SUV Survivability (Jacobsen, 2015)	Taxi Survivability (Bishop et al., 2016)
0	100%	100%	100%
1	98%	98%	99%
2	97%	96%	94%
3	95%	94%	92%
4	93%	92%	85%
5	91%	89%	78%
6	89%	87%	71%
7	86%	84%	61%
8	83%	81%	52%
9	80%	77%	45%
10	75%	72%	40%
11	69%	66%	37%
12	63%	60%	32%
13	55%	52%	22%
14	46%	44%	16%
15	36%	35%	6%
16	25%	26%	0%
17	14%	16%	0%
18	3%	6%	0%
19	0%	3%	0%
20	0%	0%	0%

Finally, the total lifetime VMT for each scenario is provided for both passenger and SAV scenarios in Table S6.3

Table S6.3 Summary of Lifetime VMT by Vehicle Scenario

	MS1: Baseline (Scrappage + Annual VMT)	MS2: Constant VMT (Average ICE)	MS3: Constant Lifetime (12 years)
ICE Car	155275	155276	158105
ICE SUV	161890	161890	167578
HEV	184752	184752	188117
EV Car	139914	155276	142464
EV SUV	148775	161890	151000
SAV Scenario	583564	-	800,915

MS1: Mileage and scrappage rates for all powertrain and vehicle types reflect estimates drawn from the NHTS and vehicle scrappage rates as described in the article and estimated with Equation 2 (main text).

MS2: BEVs and their conventional analogs are treated identically and use mileage and scrappage estimates for conventional powertrains.

MS3: Assumes the same annual VMT as MS1 and MS2 but fixes vehicle life at 12 years for all vehicle types.

Constant Lifetime (12 years)

Section S7. Electricity Generation

This section provides the complete results of the electricity generation analysis and the resulting forecast for grid carbon intensity. The study considered two regional scenarios: the California subset of the WECC region (CAMX) and a US national average. The study also considered two policy scenarios: a business as usual case and a carbon tax scenario with a $25 dollar per ton cost of carbon. The Annual Energy Outlook 2018 defines the Reference case in which: population (including armed forces overseas) grows by an average rate of 0.6%/year, nonfarm employment by 0.7%/year, and productivity by 1.6%/year from 2017 to 2050. The real gross domestic product increases by 2.0%/year from 2017 through 2050, and growth in real disposable income per capita averages 2.2%/year (U.S. Energy Information Administration, 2018).

For all scenarios, the study considered a time horizon from 2018 to 2050. Data on the net electricity generation by year by fuel source was obtained from the Annual Energy Outlook created by the Energy Information Administration. The AEO forecast is based on outputs of the National Energy Model, a large scale economic equilibrium model of energy supply and disposition (Gabriel et al., 2001).

The average net generation by fuel source is provided for a subset of years in Table S7.1.

Table S7.1 Average Net Generation by Fuel Source for Residential and Commercial End Uses

Scenario	Region	Fuel Source	2016	2020	2025	2030	2035	2040
Reference case	US-AVG	Coal	30%	28%	27%	26%	25%	24%
		Petroleum	1%	0%	0%	0%	0%	0%
		Natural Gas	34%	32%	33%	34%	34%	34%
		Nuclear	20%	18%	16%	15%	14%	14%
		Renewable Sources	15%	20%	22%	23%	26%	28%
		Other	0%	1%	1%	1%	1%	0%
	WECC-CAMX	Coal	5%	4%	0%	0%	0%	0%
		Petroleum	0%	0%	0%	0%	0%	0%
		Natural Gas	45%	33%	30%	27%	22%	20%
		Nuclear	10%	10%	5%	0%	0%	0%
		Renewables	40%	53%	65%	73%	78%	80%
$25 carbon allowance fee	US-AVG	Coal	30%	20%	9%	3%	1%	1%
		Petroleum	1%	0%	0%	0%	0%	0%
		Natural Gas	34%	40%	40%	42%	42%	39%
		Nuclear	20%	18%	18%	17%	16%	16%
		Renewable Sources	15%	22%	32%	37%	40%	43%
		Other	0%	1%	1%	1%	1%	0%
	WECC-CAMX	Coal	5%	0%	0%	0%	0%	0%
		Petroleum	0%	0%	0%	0%	0%	0%
		Natural Gas	45%	45%	30%	19%	14%	14%
		Nuclear	10%	9%	5%	0%	0%	0%
		Renewables	40%	45%	66%	81%	86%	86%

The average generation by fuel source data was combined with the life cycle emissions inventory data to estimate the emissions rates by year. For each fuel source, a regionally representative LCI was estimated using data from the GREET 1 model (Argonne National Laboratory, 2017b). Table S7.2 shows the estimated LCIs by fuel source and scenario. The final row of the table shows the estimated total greenhouse gas emissions of each kilowatt hour provided in carbon dioxide equivalents. A 100 year global warming potential is assumed, with characterization factors taken from the IPCC AR5.

Table S7.2 Life Cycle Inventory by Fuel Source and Regional Scenario

Flow	California (CAMX)				National Average (US-AVG)				Unit
	Coal	Oil	Natural Gas	Nuclear	Coal	Oil	Natural Gas	Nuclear	
Total energy	10751.1	12251.1	8402.1	3806.2	11560.4	12251.1	10246.5	3806.2	btu/kWh
Fossil fuels	10740.3	12178.1	8392.7	123.9	11548.7	12178.1	10234.9	123.9	btu/kWh
Coal	10527.7	38.7	3.9	13.8	11320.2	38.7	4.8	13.8	btu/kWh
Natural gas	43.2	832.2	8356.1	96.6	46.4	832.2	10190.3	96.6	btu/kWh
Petroleum	169.4	11307.3	32.6	13.6	182.1	11307.3	39.8	13.6	btu/kWh
VOC	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.0	g/kWh
CO	0.2	1.2	0.5	0.0	0.2	1.2	0.6	0.0	g/kWh
NOx	1.4	7.2	0.5	0.0	1.5	7.2	0.6	0.0	g/kWh
PM10	0.4	0.3	0.0	0.0	0.4	0.3	0.0	0.0	g/kWh
PM2.5	0.2	0.2	0.0	0.0	0.2	0.2	0.0	0.0	g/kWh
SOx	3.5	6.7	0.1	0.0	3.8	6.7	0.1	0.0	g/kWh
CH4	1.6	1.2	1.6	0.0	1.7	1.2	1.9	0.0	g/kWh
N2O	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	g/kWh
CO2	1069.2	1030.8	500.9	8.3	1149.7	1030.8	610.8	8.3	g/kWh
CO2 (w/ C in VOC & CO)	1069.8	1033.0	501.9	8.3	1150.3	1033.0	612.1	8.3	g/kWh
GHGs (CO_2e)	1114.0	1064.8	545.4	9.0	1197.9	1064.8	665.1	9.0	g/kWh

Finally, the estimated average carbon intensity of electricity generation for each year is provided in Table S7.3.

Table S7.3 Average Carbon Intensity of Electricity Generation by Year and Scenario

Year	California (CAMX)	US (Average)	CA ($25 C-tax)	US ($25 C-tax)
2017	296.7	525.1	297.4	522.2
2018	308.4	523.2	306.3	521.7
2019	297.1	506.5	299.5	502.1
2020	228.0	496.3	248.6	438.1
2021	216.5	485.5	220.4	408.3
2022	190.0	477.4	175.1	378.4
2023	160.3	479.6	167.6	356.2
2024	149.8	484.7	154.8	338.7
2025	166.0	487.7	163.5	322.1
2026	180.4	489.7	174.4	305.6
2027	174.7	488.1	155.0	288.7
2028	168.5	486.3	140.3	281.8
2029	161.1	485.8	125.2	278.0
2030	149.3	484.4	101.0	269.1
2031	135.0	480.8	85.2	263.9
2032	127.4	476.6	84.3	259.0
2033	123.2	473.0	82.2	254.6
2034	123.8	471.0	78.8	250.2
2035	120.8	467.0	77.8	246.7
2036	117.9	465.7	77.0	243.3
2037	114.7	463.3	77.0	240.1
2038	112.4	460.5	77.1	235.1
2039	112.8	458.3	75.2	231.0
2040	109.3	456.0	73.7	225.6
2041	108.8	454.1	72.4	220.0
2042	108.4	451.3	69.8	214.0
2043	107.2	449.3	69.8	211.4
2044	105.7	448.3	69.5	208.2
2045	104.0	445.9	69.6	204.7
2046	98.7	442.3	70.1	200.4
2047	97.1	440.0	70.5	196.3
2048	96.3	437.9	70.7	191.5
2049	96.7	437.0	70.4	185.5
2050	94.8	436.6	70.9	184.0

Section S8: Full Results

This section provides a table view of the complete results of the final GHG estimates.

Beginning on the next page, table S8.1 contains per mile GHG emissions attributable to vehicle and battery for each vehicle design scenario. The results in table 8.1 for per mile emissions attributable to production of vehicle and battery systems use the survivability method for estimating lifetime vehicle miles. The results are moderately reduced in the VMT scenario due to the assumed higher lifetime vehicle miles travelled. The phase column corresponds with the key categories of emissions in producing the vehicle and battery system. The survival and VMT methods result in the same estimated emissions rate for conventional ICE vehicles as the ICE vehicle is the basis for the VMT method used in the BEV cases.

Table S8.2 shows the use-phase LCGHG emissions per mile for each vehicle and grid scenarios. The range of values provided in table 8.2 reflect the variability associated with uncertainty in the vehicle lifetime (8 to 12 years on average). The emissions rate decreases as the vehicle life decreases as the service life increases due to the (generally) decreasing carbon intensity of the grid. But the extent of this effect diminishes with the decreasing annual mileage.

Table S8.3 provides the total results, which are the sum of the vehicle and battery emissions with the use phase emissions. As such, the total results are presented by grid scenario and service life in years. Table S8.3 makes clear the key trend, namely the increasing share of production emissions in life cycle emissions and per mile emissions for passenger vehicles.

Table S8.1 Battery and Vehicle GHG Emissions (g CO_2-e / mile) by Vehicle and Utilization Scenario

Description	ICE LDV	ICE SUV	HEV	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV	SAV ICE-SUV	SAV HEV	SAV LR-EOV	SAV LR-PLS	SAV LR-PSUV
Body and Powertrain Materials	32.7	34.9	24.5	28.6	29.7	53.0	57.8	29.7	53.0	57.8	29.7	53.0	57.8	9.7	7.8	7.1	12.7	14.7
Glider Assembly	4.8	4.6	4.0	5.3	5.3	5.3	5.0	5.3	5.3	5.0	5.3	5.3	5.0	1.3	1.3	1.3	1.3	1.3
End of Life	1.4	1.4	1.2	1.6	1.6	1.6	1.5	1.6	1.6	1.5	1.6	1.6	1.5	0.4	0.4	0.4	0.4	0.4
Battery Materials	0.3	0.4	1.3	10.6	23.3	36.8	33.8	15.5	24.5	22.4	25.0	36.0	47.4	0.1	0.4	15.5	22.3	28.2
Battery Production	-	-	-	3.0	7.9	13.2	12.4	7.4	12.3	11.6	12.3	15.4	20.3			7.6	9.5	12.0
Use (Survival - CAMX)	420.9	462.5	301.2	71.4	67.6	87.0	89.7	45.1	50.1	57.2	51.9	63.0	72.6	462.5	301.2	49.2	59.7	70.2
Use (VMT - CAMX)	420.9	462.5	301.2	72.4	68.6	88.2	91.0	45.9	51.0	57.8	52.9	64.2	73.4	462.5	301.2	54.3	66.0	77.6
Use (12 Years-CAMX)	413.4	446.8	295.8	69.1	65.5	84.2	88.4	43.2	48.0	55.8	49.7	60.4	70.8	337.0	219.5	44.7	54.2	63.8
Use (Survival - USAVG)	420.9	462.5	301.2	169.7	160.7	206.7	213.8	150.0	166.6	190.5	172.6	209.6	241.7	462.5	301.2	156.7	190.2	223.8
Use (VMT - USAVG)	420.9	462.5	301.2	194.4	165.9	213.3	217.0	154.8	172.0	193.5	178.1	216.3	245.4	462.5	301.2	158.6	192.6	226.5
Use (12 Years - USAVG	413.4	446.8	295.8	158.9	150.6	193.6	203.8	140.8	156.5	182.2	162.1	196.8	231.0	337.0	219.5	145.7	177.0	208.2

Table S8.2 Sensitivity of LCGHG Emissions to Vehicle Lifetime Assumption (8 to 20 years) by Vehicle and Utilization Scenario (g CO_2-e / mile)

	Grid Scenario	EOV	PLS	PSUV
2018	Average US Grid	255 - 215	360 - 295	374 - 306
	Average US Grid with $25 C-tax	231 - 173	329 - 241	341 - 249
	Average California Grid	167 - 119	246 - 171	254 - 175
	Average California Grid with $25 C-tax	168 - 115	247 - 166	255 - 170
2025	Average US Grid	235 - 198	303 - 245	335 - 273
	Average US Grid with $25 C-tax	171 - 131	233 - 171	253 - 187
	Average California Grid	131 - 92	189 - 128	201 - 136
	Average California Grid with $25 C-tax	122 - 82	178 - 116	189 - 122
2025 Long Range	Average US Grid	250 - 209	331 - 270	393 - 318
	Average US Grid with $25 C-tax	184 - 140	251 - 186	298 - 219
	Average California Grid	143 - 100	201 - 137	240 - 161
	Average California Grid with $25 C-tax	134 - 89	189 - 124	226 - 145

Table S8.3 Total GHG Emissions by Grid and Vehicle Scenario

Grid Scenario	Service Life (Years)	Leaf (2012)	EOV	PLS	PSUV	2025 EOV	2025 PLS	2025 PSUV	2025 LR-EOV	2025 LR-PLS	2025 LR-PSUV	SAV LR-EOV	SAV LR-PLS	SAV LR-PSUV	Unit
CAMX	8	139	160	237	244	125	181	193	137	192	229	75	97	139	g CO2e/mile
CAMX	12	117	132	192	197	102	143	153	110	153	181	65	84	117	g CO2e/mile
CAMX	16	104	116	166	170	89	123	131	96	132	155	59	76	104	g CO2e/mile
CAMX	20	95	104	150	92	81	110	71	52	71	139	56	71	95	g CO2e/mile
USAVG	8	220	238	336	349	217	283	312	232	308	365	170	213	220	g CO2e/mile
USAVG	12	207	217	302	313	199	252	279	211	276	325	166	206	207	g CO2e/mile
USAVG	16	200	206	283	293	189	234	261	200	258	304	163	202	200	g CO2e/mile
USAVG	20	195	199	271	169	183	224	150	115	148	290	161	199	195	g CO2e/mile
CAMX-$25C	8	140	161	238	245	117	172	182	128	182	217	67	87	140	g CO2e/mile
CAMX-$25C	12	117	131	191	196	92	132	140	100	141	167	55	72	117	g CO2e/mile
CAMX-$25C	16	101	112	162	165	79	112	118	85	119	140	49	63	101	g CO2e/mile
CAMX-$25C	20	90	99	143	87	70	99	63	46	63	123	45	58	90	g CO2e/mile
USAVG-$25C	8	201	220	313	324	161	220	238	173	237	282	112	142	201	g CO2e/mile
USAVG-$25C	12	175	187	263	271	139	184	201	149	200	236	104	130	175	g CO2e/mile
USAVG-$25C	16	159	168	234	241	126	164	179	135	179	210	98	123	159	g CO2e/mile
USAVG-$25C	20	149	155	215	133	118	151	100	75	99	193	94	117	149	g CO2e/mile

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